CREDIT CONSTRAINTS: THEIR EXISTENCE, DETERMINANTS, AND IMPLICATIONS FOR U.S. FARM AND NONFARM SOLE PROPRIETORSHIPS

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The objective of this study is to determine the effect of credit constraints on production for farm and nonfarm sole proprietorships. A propensity score-matching estimator is employed to provide unbiased estimates of the production impacts of being denied credit. The empirical results demonstrate that the value of production is significantly lower for credit-constrained sole proprietorships. If this drop in the value of production is aggregated to a national level, it constitutes only 3% and 13% of total value of production for farm and nonfarm sole proprietorships, respectively.

Key words: credit constraint, debt, farm credit, propensity score-matching.

Numerous studies have examined the existence and importance of credit constraints (for a survey, see Browning and Lusardi 1996). Many of these studies have focused on developing countries with immature credit markets, where credit access is thought to be more limited, and significant implications for economic development and growth exist. When capital markets are imperfect, individuals cannot borrow freely at the current interest rate. Capital market imperfections can suppress the aggregate accumulation of capital, the rate of return on investments, technology adoption, and productivity (Hubbard and Kashyap 1992; Saha, Shumway, and Talpaz 1994; Vasavada and Chambers 1996; Bierlen and Featherstone 1998; Barry, Bierlen, and Sotomayor 2000). Limited access to credit also influences a household's well-being. Phimister (1995), Barry and Robison (2001) and Blancard et al. (2006) found that farms—and Jefferson (1997) found that entrepreneurs—benefit in additional consumption and/or investment from relaxed borrowing constraints. At the individual household level credit constraints can affect resource allocation decisions and have important consequences for policy outcomes. In agricultural policy, for instance, distortions in farm capital markets can lessen the intended separability between decoupled payments and agricultural production (Barnard et al. 1997, 2001; Collender and Morehart 2004).

When estimating the impact of credit constraints, one must deal with potential selection bias. Selection bias arises in credit markets because people are not randomly assigned to treatment (credit-constrained) and control (not credit-constrained) groups. Rather, this sorting or selection into treatment and control groups is dependent on characteristics of the applicant. Within the literature, different statistical methods have been employed to control for this selection bias. Petrick (2004) found that being credit-constrained lowered output production via the Heckman estimator. Feder et al. (1990), Carter and Olinto (2003) and Foltz (2004) used switching regressions to demonstrate the impacts of credit constraints on production, investment and profits, and investment, respectively. To control for selection bias in our study, we employ a propensity score-matching estimator. To our knowledge this is the first study to use such an estimator to control for credit market selection bias.

This study's objective is to determine the effect of credit constraints on production for farm and nonfarm sole-proprietorship households. Through this analysis, we identify how farm and nonfarm sole proprietorships are both similar and different relative to credit use and credit availability. Our examination of these different types of sole proprietorships is

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unique because it utilizes data from two national surveys: the Survey of Consumer Finances (SCF) and the Agricultural Resource Management Survey (ARMS). In the past SCF has asked respondents to answer questions regarding their use of and access to credit. Similar credit questions were included in the 2005 ARMS, thus allowing for construction of the data used in this study. Furthermore, these questions allow us to adopt the direct approach of Jappelli (1990) to identify treatment and control groups based on self-reported responses to questions about credit access.[1]

Five credit access and use classes are identified for farm and nonfarm sole proprietorships. In our study proprietors that received credit without issue is the control group, and those proprietors that were turned down for credit are the treated group. Jappelli (1990) argues that individuals who did not apply for credit because of the fear of denial are similar to those that were turned down for credit and should be included in the treated group. Jappelli then classifies all other individuals as not being credit-constrained (i.e., his control group). Through propensity score-matching, we demonstrate that using the Jappelli (1990) classification underestimates the effect of credit constraints on production for farm and nonfarm sole proprietorships. This empirical result highlights the problem if there is a contamination of the control group. In Jappelli's classification this contamination occurs because sole proprietorships that were initially denied credit but later received credit and those who no longer need credit are included in the control group.

A key contribution of this article is the use of the propensity score-matching estimator to properly measure and estimate the production impacts of being credit-constrained. The results demonstrate that the impact of being credit-constrained significantly lowers production. Most farms and businesses that are credit-constrained tend to operate small-scale farms or businesses. For small or beginning farms and businesses, having access to credit is important because even a small decrease in production can be detrimental to the financial viability of the business. This result supports the Farm Service Agency (FSA) and Small Business Administration (SBA) programs that assist businesses in need of credit or unable to find credit from a lender. Finally, we demonstrate the flexibility of the propensity score-matching method by segmenting the data by production specialty and illustrating the negative impacts of being credit-constrained on another outcome variable of interest—consumption.

A Theoretical Model of Credit Constraints

Our primary interest is the impact of being credit-constrained on production. These impacts on production have important implications for policy, but as we demonstrate below, our empirical application is flexible enough to consider other outcome variables of interest (e.g., consumption). To conceptualize the impact of credit constraints on sole proprietorships, we draw from the well-developed theoretical literature on neoclassical producer-consumer models (Petrick 2004; Bezuneh, Deaton, and Norton 1988; Singh, Squire, and Strauss 1986). Also, this producer-consumer model is general enough to encompass nonagricultural sole proprietors.

A household maximizes consumption c via the following intertemporal, additive utility model in periods 0 and 1, given a set of exogenous household characteristics z^h; $u(c_0, c_1; z^h)$, where $u(.)$ is assumed to be twice differentiable and quasi-concave, and exogenous household characteristics consist of age, location, etc. To simplify the explanation, all revenue-generating activities, production and nonbusiness activities O are assumed to occur in period 1, and a variable input x used in producing good q is purchased at a given price p in period 0 with liquid funds a or borrowed funds B. Borrowed funds are repaid with interest r in period 1. All other variable inputs are either ignored or held fixed in producing q. The household production follows a concave production function $q = f(x; z^q)$, where z^q represents fixed and exogenous inputs such as land, machinery, tools for manufacturing, etc. In the following formal producer-consumer model, all prices are normalized by output price.

A borrowing constraint $\bar{B}(z^h, z^q)$ is added to period 0 and is a function of household and production characteristics (i.e., z^h and z^q). Whether or not this constraint holds depends on supply and demand for credit. In this case interest rates are the price of credit, the supply and demand curves respectively reflect the amount lenders are willing to lend and borrowers are willing to borrow at exogenously

[1] An alternative, indirect approach that is widely used infers the presence of credit constraints from violations of the assumptions of the life-cycle or permanent income hypothesis.

determined interest rates. Households will pursue credit up to some limit. This limit may be imposed by a lender or may be the result of self-limiting behavior. Asymmetry of information between borrower and lender gives rise to differences in these two limits. For example, a household may not apply for credit because of the fear of denial. Another situation where asymmetry of information exists is when borrowers wish to borrow more than their credit limit allows, which is commonly known as credit rationing. Credit rationing also creates the situation where some borrowers may receive credit while other borrowers with similar financial characteristics may not. The potential for adverse selection arising from the asymmetry of information between the lender and the borrower discourages lenders from using the interest rate as a way to ration credit (Stiglitz and Weiss 1981).

The formal producer-consumer model is as follows:

$$(1)\qquad \max_{c_0>0, c_1>0, x>0, B\geq 0} u\left(c_0, c_1; z^h\right)$$

s.t.

$$(2)\qquad a + B - c_0 - px = 0$$

$$(3)\qquad f\left(x; z^q\right) + O - c_1 - (1+r)B = 0 \quad \text{and}$$

$$(4)\qquad \bar{B}\left(z^h, z^q\right) \geq B.$$

Equation (1) represents the choices the producer-consumer will make to maximize $u(\cdot)$. Equations (2) and (3) represent the budget constraints for periods 0 and 1, respectively, and equation (4) is the credit constraint. To demonstrate the impact that being credit-constrained has on production, we first solve equations (1)–(4) for optimal production when credit is not constrained:[2]

$$(5)\qquad \frac{\partial f(\cdot)}{\partial x} = p(1+r).$$

Since x is purchased before revenues are earned, p must be inflated by r. Let the optimal input from equation (5) be denoted as x^*_{nc}.

Now let us solve equations (1)–(4) when the producer-consumer is credit-constrained or $\bar{B}(z^h, z^q) = B$:

$$(6)\qquad \frac{\partial f(\cdot)}{\partial x} = p\left((1+r) + \frac{\eta}{\lambda}\right)$$

where η and λ are the Lagrangean multipliers associated with the borrowing constraint in period 0 and the budget constraint in period 1, respectively. Ignoring degeneracy of the credit constraint, we assume that each Lagrange multiplier is strictly positive, and the present value opportunity cost of the optimal input for the credit-constrained producer-consumer (denoted as x^*_{cc}) is greater than the present value opportunity cost found in equation (5).

Since x^*_{cc} has a higher present value opportunity cost than x^*_{nc} and the production function is concave, $x^*_{nc} > x^*_{cc}$ must hold. This is the case because the credit-constrained producer-consumer will lower her/his amount of x to increase the value of marginal product. Therefore, the production of a credit-constrained producer-consumer will be lower than the production of a noncredit-constrained producer-consumer. Much like production, consumption is negatively impacted by credit constraints. A credit-constrained producer-consumer will have a lower marginal utility from consumption than will her/his noncredit-constrained counterparts.

One cannot estimate a reduced form output supply function without accounting for both household and production characteristics because production and consumption decisions are not separable (Petrick 2004). Petrick estimates the impact of being credit-constrained on production through a Heckman two-step estimator. In his model the first step is a probit regression showing whether or not a household is credit-constrained, and the second step is an estimation of the reduced form output supply function that accounts for both household and production characteristics. Others have used methods similar to Petrick's to determine the impact of credit constraints on production and consumption for an agricultural household, and Jappelli (1990) and Crook (1996) estimated the impact of being credit-constrained on consumption for nonagricultural households.

A sole proprietorship is considered to be credit-constrained if equation (4) is binding or the demand for credit exceeds the supply of credit. Therefore, the probability a household is credit-constrained is modeled by Petrick (2004), Jappelli (1990) and Crook (1996) as $\pi = 1$ if a credit constraint exists and $\pi = 0$ if not. However, the sole proprietor may choose B

[2] Here is the Lagrangean equation used to solve the producer-consumer problem: $L = u\left(c_0, c_1; z^h\right) + \mu(a + B - c_0 - px) + \lambda(f(x; z^q) - c_1 - (1+r)B) + \eta(\bar{B}(z^h, z^q) - B)$.

to be zero, or the demand for credit may be zero. Cox and Jappelli (1993) considered this issue and concluded that the state of credit constraint is more complex than the distinction $\pi = 0$ or $\pi = 1$, which suggests both demand and supply credit factors impact π.

Like Jappelli, Pischke, and Souleles (1998), we employ a direct method of assessing whether or not a household is credit-constrained. Our article extends their work and the work of Petrick (2004), Jappelli (1990) and Crook (1996) first by analyzing different classifications of credit-constrained sole proprietorships and then by estimating and comparing the different impacts those classifications have on production via the propensity score-matching estimator. To account for different credit access and use classes, we assume that each situation is distinct and observable. The five credit access and use classes are: (1) did apply and received credit; (2) did not apply for credit; (3) were initially denied credit but obtained credit after multiple attempts; (4) did not apply for credit for fear of denial (i.e., discouraged credit applicants); and (5) were turned down for credit. Jappelli and Crook argue that discouraged credit applicants and those turned down for credit are not different. Therefore, these two classes comprise $\pi = 1$, and the other three fall into $\pi = 0$. We contend that this definition of credit-constrained and not credit-constrained underestimates the effect of credit constraint on the value of production because there is a contamination of the control group. A contamination of the control group (not credit-constrained) can occur if those who were treated (credit-constrained) but later receive credit, and those who no longer need credit are included in the control group. Therefore, we segment the data by the five classes described above. To test the impacts of credit constraints on production for nonagriculture and agriculture sole proprietors, an extensive and unique data set is necessary. The SCF and the ARMS data pose questions that allow the identification of the five credit access and use classes and provide enough complementary information to compare the two types of sole proprietors.

Data

To meet our objectives, a sample of farm and nonfarm households who own and operate sole proprietorships must be constructed so that similar credit-constrained households can be identified. In 2005, a set of credit-related questions like those used in the SCF were added to the ARMS. This addition allowed samples that are comparable in information content but reference different time periods. The SCF is a cross-sectional survey conducted every three years by the Federal Reserve System Board of Governors. The latest survey available is for 2004. The SCF provides a wide array of household and business characteristics and uses a dual frame sample design to improve coverage of all households in the United States. Similar to the SCF, the ARMS data set contains all of the necessary information to compare farm households and nonfarm households. ARMS is a complex survey design where each observation in the ARMS data set represents a number of similar farm households or the inverse probability of the surveyed household being selected for the survey. Given the complex design of each survey, all standard errors for the SCF are estimated using the repeated information inference technique (Montalto and Yuh 1996). For the ARMS all standard errors are estimated using the delete-a-group jackknife variance estimator (Kott 1998).

Unfortunately, creating a comparable sample is not a straightforward task, given the lack of direct correspondence between business ownership and self-employed status in the SCF (Hurst and Lusardi 2004). In the 2004 SCF, self-employment status results from a question asking whether the household head works for her/himself or someone else. Excluding farms, over 12 million self-employed households exist whose business owners have either an active or passive role in the management of the business. Further restricting the SCF data to include only those business owners with an active management role, the original population of nonfarm, self-employed owners further reduces the 2004 sample to 1,560, representing 5.8 million households. Restricting the SCF in this manner makes it comparable to farm sole proprietorships because the 2005 ARMS sample only considers farmers who own and actively manage their farm operation. The 2005 ARMS sampled 5,411 farm sole proprietors, representing 1.9 million farm households.

Each survey used a simple, unambiguous method for identifying credit constraints at the household level. The questions were designed to capture all aspects of credit use and sources of constraints on credit access, providing a comprehensive approach to identifying credit-constrained businesses. Jappelli (1990), Feder et al. (1990), Cox and Jappelli (1990, 1993) and Jappelli, Pischke, and Souleles (1998) have found support for using directly elicited credit constraints to model the effects of being credit-constrained on consumption, investment decisions and an explanation of why households are credit-constrained. We have created an appendix (Briggeman, Towe, and Morehart 2008) to show each set of questions as they appeared in the SCF and ARMS and how the classes are created. Now, our focus is on differences between the five credit access and use classes.

Descriptive Statistics of the Credit Access and Use Classes

Based on the survey responses, sole proprietorships were classified into five credit access and use classes. Figure 1 shows that the proportion of households that use credit without issue (class 1) is nearly identical at 54% for farm and nonfarm sole-proprietorship households. More than two times as many farm households had no debt or did not apply (class 2) compared to nonfarm sole-proprietorship households (15%). Seven percent of nonfarm sole-proprietorship households obtained credit after multiple attempts (class 3), as compared with 5% of farm households. The share of discouraged borrowers (class 4) was substantially higher for nonfarm sole-proprietorship households at 16%, as compared with only 2% of farm households. Finally, 3% of farm households reported being denied credit (class 5), as compared with 8% of nonfarm sole-proprietorship households.

Comparing the means of selected variables in table 1 for farm and nonfarm sole proprietorship households yields some striking similarities and differences. As argued in the theoretical section, a credit-constrained household has lower production. Based on the available information from the two different data sets we evaluated, the best proxy for production is the value of production (*VPROD*), which is gross revenue from annual production. Petrick (2004) uses a similar measure in his output supply equation. For both data sets *VPROD* is highest for both farm and nonfarm sole proprietorships that are not credit-constrained. Based on the theoretical model, it is expected that credit-constrained households will have a lower *VPROD*. The following variable discussion covers those variables used in the first stage of the propensity score-matching estimator, which is a logit regression of the probability a household is credit-constrained.

Average household income (*HHINC*) was about $9,000 higher for nonfarm, sole-proprietorship households than for farm

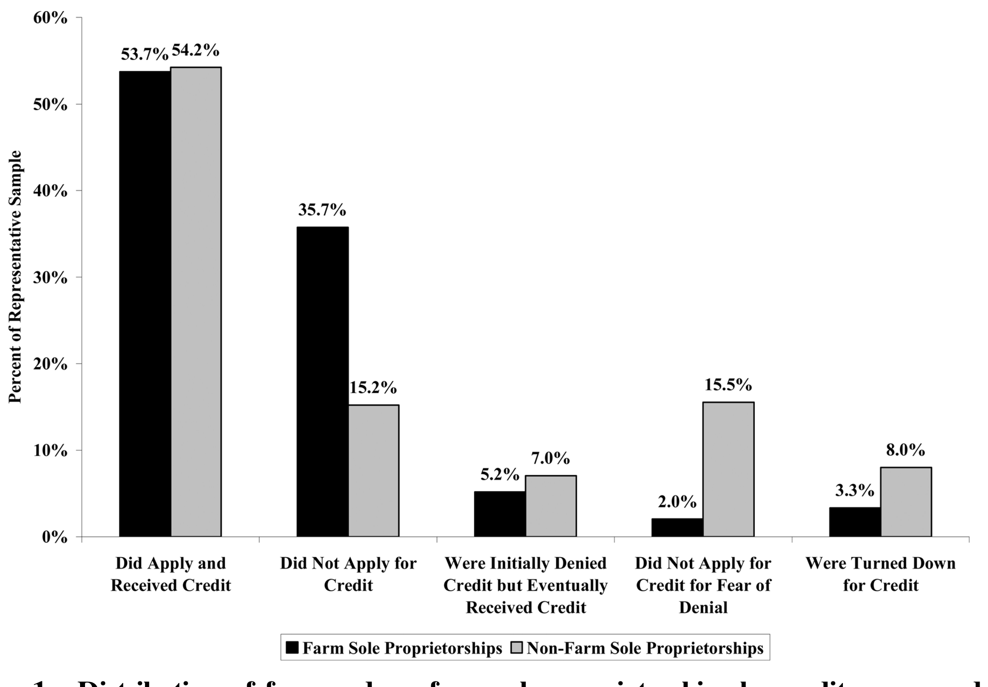

Figure 1. Distribution of farm and nonfarm sole proprietorships by credit access and use classes

Table 1. Variable Definitions and Descriptive Statistics for Farm and Nonfarm Sole Proprietorships by Credit Access and Use Classes

		Credit Access and Use Classes for Small Business Owners[a]						Credit Access and Use Classes for Farm Owners[a]				
Variable Definition	All Business	1	2	3	4	5	All Farms	1	2	3	4	5
Value of production	$108,712	$131,053	$115,660	$75,085	$63,796	$60,920	$58,914	$83,559	$24,642	$53,665	$40,369	$48,531
	(13.54)	(16.20)	(39.02)	(39.90)	(39.01)	(40.93)	(29.20)	(7.40)	(7.70)	(291.20)	(76.90)	(17.70)
Household income[2]	$81,426	$97,236	$85,952	$63,347	$45,579	$51,190	$72,541	$83,473	$61,571	$67,211	$46,918	$37,761
	(7.50)	(7.50)	(28.40)	(28.40)	(11.60)	(15.70)	(6.20)	(4.30)	(5.30)	(57.80)	(22.70)	(15.42)
Business net worth[2]	$152,596	$193,611	$178,176	$84,438	$65,920	$54,339	$596,608	$627,087	$555,377	$821,814	$429,872	$299,115
	(27.20)	(30.00)	(73.20)	(61.10)	(26.90)	(35.70)	(4.10)	(4.60)	(5.90)	(50.70)	(14.10)	(11.50)
Working capital divided by monthly expenditures	4.9	3.7	15.5	4.5	1.2	0.6	9.2	7.6	12.1	6.7	11.4	5.7
	(16.30)	(11.60)	(21.00)	(33.60)	(29.00)	(26.00)	(6.40)	(7.40)	(5.50)	(49.80)	(20.10)	(12.80)
Total operator spouse labor hours	3,099	3,320	2,108	3,719	3,012	3,106	3,799	4,444	2,936	3,559	2,583	3,761
	(5.10)	(3.20)	(11.30)	(7.00)	(8.30)	(9.50)	(4.10)	(2.00)	(3.30)	(44.20)	(17.50)	(6.40)
Total weeks spent by operator and spouse working away from the business	17	20	10	28	12	16	25	31	17	24	16	25
	(6.40)	(7.30)	(24.80)	(19.40)	(20.00)	(25.30)	(5.70)	(4.10)	(7.40)	(46.20)	(29.10)	(12.20)
Number of years owning and operating the business	13	14	18	11	9	7	24	22	30	23	15	13
	(4.70)	(5.80)	(10.20)	(12.80)	(12.60)	(17.20)	(2.30)	(2.70)	(2.10)	(18.20)	(15.30)	(11.00)
Household head's age in years	50	51	60	43	42	45	57	54	64	56	59	51
	(1.50)	(1.80)	(3.20)	(5.30)	(4.80)	(6.0)	(0.80)	(1.00)	(0.70)	(4.10)	(7.10)	(3.30)
Number of dependents	1.1	1.1	0.4	1	1.6	1.3	1.4	1.5	1.2	1.4	1.3	1.8
	(6.00)	(8.50)	(24.80)	(28.20)	(15.40)	(17.90)	(1.80)	(2.90)	(2.10)	(14.50)	(13.10)	(10.00)
Number of business employees	2.5	2.8	1.8	2.6	2	2.7	1.2	1.2	1.1	1.2	1.4	1.2
	(14.70)	(21.00)	(14.60)	(25.60)	(14.40)	(38.10)	(33.70)	(2.00)	(1.00)	(323.30)	(13.60)	(6.10)
Number of loans	5	6.3	3.7	4.2	3.3	2.9	1.4	2.1	0	1	3.5	3.2
	(4.80)	(5.10)	(15.20)	(14.20)	(17.20)	(20.20)	(4.70)	(2.30)	(na)	(49.50)	(8.10)	(9.50)
Expected sale price of dwelling	$227,973	$280,538	$239,739	$152,750	$78,637	$205,513	$135,262	$142,961	$124,630	$149,139	$128,152	$107,925
	(7.70)	(8.10)	(23.10)	(30.40)	(26.10)	(33.30)	(14.70)	(21.00)	(14.60)	(25.60)	(14.40)	(38.10)
Dummy variable with 1 being operator and spouse do not have a college education; 0 otherwise	73.50%	66.20%	77.50%	68.10%	90.00%	88.40%	87.00%	84.70%	89.30%	85.40%	91.90%	97.80%
Dummy variable with 1 being household head is single; 0 otherwise	28.80%	21.90%	34.70%	44.30%	47.50%	19.40%	18.50%	15.70%	22.30%	17.60%	28.30%	18.60%
Reported sample size[3]	1,560	924	267	114	155	100	5,411	3,423	1,390	299	105	194
Weighted or representative sample size	5,855,852	3,175,040	890,159	412,673	909,354	468,627	1,915,726	1,029,329	684,676	99,088	38,812	63,821

Note: [a] Credit access and use classes 1–5 are represented as follows: (1) did apply and received credit; (2) did not apply for credit; (3) were initially denied credit but obtained credit after multiple attempts; (4) did not apply for credit for fear of denial; and (5) were turned down for credit.

[b] Household income and business net worth are presented in natural form to aid in interpretation of the differences across classifications; however, the regression uses the natural log.

[c] Per Montalto and Sung (1996) and the SCF codebook, reported sample size for small business owners includes the five implicate replications.

Standard errors are in parentheses and and data sources are 2004 Survey of Consumer Finance for nonfarm proprietors and 2005 Agricultural Resource Management Survey for farm proprietors.

households. Documentation has shown that farm households have more business equity (*BUSNW*) relative to their nonfarm counterparts (Mishra et al. 2002). The results in table 1 are similar because all farm credit access and use classes have a higher *BUSNW* than their nonfarm counterparts. Based on the theoretical model and empirical evidence, it is expected that *HHINC* and *BUSNW* will negatively impact the probability of being credit-constrained.

The proxy for liquidity used in this study is the liquidity reserve ratio (*LIQRESV*). This ratio measures how much cash and liquid assets a sole proprietorship has available after paying current debts relative to its monthly expenditures. The turned down for credit proprietors' *LIQRESV* as well as their *BUSNW* are the lowest across all classes. Also, all credit access and use classes for farms have more liquidity reserve than their nonfarm counterparts. This may be the result of precautionary saving that is more prevalent for farm households relative to nonfarm households (Mishra et al. 2002). Based on the theoretical model, *LIQRESV* is expected to negatively impact the probability of being credit-constrained.

The average years of owning and operating the business (*YRBUS*) is lower for all credit access and use classes of nonfarm sole proprietorships relative to farm sole proprietorships. The age of farm operators has been increasing over time (Hoppe et al. 2001), which may explain why the average household head's age (*AGE*) for farms is higher than nonfarms. Number of employees (*EMPLNUM*) and expected sale price of dwelling (*EXPSALP*) for all classes of nonfarm sole proprietors exceed their farm counterparts. Among nonfarm proprietors, number of loans (*NUMLOAN*) is the lowest for the turned down for credit class (2.9); among farm proprietors, however, the *NUMLOAN* for the turned down for credit class (3.2) is the second highest average. A potential reason why the turned down for credit farm proprietors have more loans than the other farm proprietor classes is they had outstanding loans before they were turned down for credit, which may have led to them being denied credit. All of these variables do not provide clear expected effects on the probability of being credit-constrained.

Farm sole proprietorships have a higher average of household heads or spouses who do not have a college education (*NOCOLLEGE*). Fewer nonfarm household heads are not married (*NOMARRIED*), while a larger number of farm and nonfarm household heads who are not married are classified as discouraged credit applicants. It is not clear what the expected effect should be for *NOCOLLEGE* and *NOMARRIED* on the probability of being credit-constrained.

The descriptive statistics for farm and nonfarm sole proprietorships suggest that survey questions added to the ARMS yield similar results relative to the established questions on the SCF.[3] Do household decisions and the resulting economic outcomes measured by *VPROD* affected by credit use and availability? To answer this question, we employ propensity score-matching.

Propensity Score-Matching

As mentioned previously, we test the production impact of being credit-constrained in the context of a nonrandom selection problem. In this framework we test for and measure the treatment effect on the observation of interest. In our context the treatment is the turned down for credit class (class 5 discussed earlier); the control is the applied and received credit class (class 1 discussed earlier); and the outcome of interest is the value of production from the business entity. Our treatment/control definition is then compared to Jappelli's or the turned down for credit class and did not apply for fear of denial credit class being the treatment group and all other classes making-up the control group. By not combining the classes, like Jappelli (1990), potentially biased estimates are avoided. In addition, we expect comparisons between denied credit and received credit without issue to exhibit the largest production impact or an upper bound of being credit-constrained. Assigning a survey respondent to the treated class is a nonrandom selection process because sole proprietorships that are credit-constrained are likely to have, on average, different characteristics from sole proprietorships that are not credit-constrained, and these characteristics may alter the dollar value of output produced.

The maximum likelihood Heckman procedure controls for selection bias by jointly estimating the outcome and treatment equations, but the procedure relies on a joint normality

[3] Moreover, the credit-constrained groups are distinct and identifiable within each survey. A multinomial logit model was estimated, and the results confirm that the presented credit constraint groupings are significantly different and identifiable based on the covariates presented in table 1.

assumption between the residuals. In the last decade an alternative method to estimating the outcome and treatment equations has gained popular support—propensity score-matching. This procedure estimates treatment effects by matching treated and untreated observations, controlling for distributional differences using conditioning variables. Matching methods allow nonparametric estimation of treatment effects, removing sensitivity to functional form and exposing violations of the common support—cases where treated observations are substantially different from untreated observations. In the context of conventional regression-type analysis, violations of the common support remain undetected and can result in treatment effects being extrapolated solely on the basis of functional form because nontreated observations that are similar to treated ones do not exist.

Here, we draw on a class of estimators called propensity score-matching estimators, first suggested by Rosenbaum and Rubin (1983). Applications of propensity score-matching are now quite prevalent in the literature, especially in labor economics where the evaluation of job training programs represents a significant challenge (such as Heckman, Ichimura, and Todd 1997; Dehejia and Wahba 2002; Lechner 2002; Smith and Todd 2005a).

Rosenbaum and Rubin (1983) identify an outcome of interest, which is derived from the following equation:

$$(7) \qquad E(Y_1 - Y_0 \mid D = 1) = E(Y_1 \mid D = 1) - E(Y_0 \mid D = 1)$$

where Y is the outcome variable of interest, in our case the value of production, and D indicates to which group, control or treated, the observation belongs. The subscript and D value of 1 indicates the observation is treated, or denied credit, and 0 is the control group, or received credit. Therefore, the outcome of interest is the average difference in Y_1 and Y_0. Since an observation can be in only one state, treated or control, the matching procedure attempts to estimate $E(Y_0 \mid D = 1)$, which is known as the counterfactual and is unobservable. In our case, the challenge is to estimate the impact of being denied credit on the value of production for those sole proprietors who actually received credit.

If observations were randomly assigned to treated and control groups, then on average one would expect control observations to have the same outcome level as treated observations, assuming they were assigned to the treated group. In this case the best estimate of the average treatment effect is simply $E(Y_1 \mid D = 1) - E(Y_0 \mid D = 0)$. In our case individuals are not randomly assigned to treated and control groups. In other words there is a systematic way in which observations are deemed to be creditworthy; thus, the average treatment effect cannot be estimated as discussed above.

Rosenbaum and Rubin (1983) proposed a method to resolve this issue of observations not being randomly assigned to treatment and control groups. They argue that if treatment is determined by some set of covariates Z one can establish a control group that is similar in Z relative to the treatment group. They formally state this as

$$(8) \qquad E(Y_1 - Y_0 \mid Z, D = 1) = E(Y_1 \mid Z, D = 1) - E(Y_0 \mid Z, D = 1).$$

Matching estimators pair each treated observation with 1 or more observationally similar nontreated observations, using the conditioning variables Z to identify their similarity. This procedure is justified if the outcomes are independent of the selection process after conditioning on the covariates in Z. That is, if those observations found in the set $D = 0$ were actually treated, the expected value of their outcomes, once conditioned on the Z's, would not differ from the expected value of outcomes in the treated group. More precisely, conditional mean independence is required, such that:

$$(9) \qquad E(Y_0 \mid Z, D = 1) = E(Y_0 \mid Z, D = 0).$$

Direct implementation of the above equation would be difficult for a large number of conditioning variables, yet ensuring that equation (9) holds would typically require a rich set of these variables. Rosenbaum and Rubin (1983) defined the propensity score-matching estimator by showing that instead of conditioning on all K elements of the Z vector, one can equivalently condition on a one-dimensional function of that vector. They show that if outcome Y_0 is independent of selection when conditioned on the Z's, then it is also independent of selection when conditioned on the propensity score $P(Z)$, which is defined as the probability of selection conditioned on the Z's or more formally:

$$(10) \quad P(Z) \equiv \Pr(D = 1 \mid Z).$$

Rosenbaum and Rubin also state that there is no single Z or combination of Z variables that guarantees treatment. Put another way, for any set of Z variables, the probability of treatment is strictly greater than 0 and less than 1, that is, $0 < \Pr(D = 1 \mid Z = z) < 1$ for $z \in \tilde{\mathbf{Z}}$. This condition must be true for each treated observation to have the potential of an analogue among the untreated. Thus, the impact of being treated is only valid for observations within the common support, or the propensity scores for treated and control observations are positive and the distributions of these propensity scores for treated and control observations intersect.

Equation (8) can now be rewritten to show the average treatment effect of the treated (ATT):

$$(11) \quad \begin{aligned} ATT &= E(Y_1 - Y_0 \mid P(Z), D = 1) \\ &= E(Y_1 \mid P(Z), D = 1) \\ &\quad - E(Y_0 \mid P(Z), D = 0). \end{aligned}$$

In practice (10) is estimated as a binary probit or logit, with the treatment dummy as the dependent variable. Explanatory variables include factors that are expected to affect the probability of treatment and those that are expected to affect outcomes directly and may be correlated with treatment. This works well in our setting because many empirical studies have found significant variables that explain why an individual or business is denied credit (many of these variables were discussed in the data section). The last term in (11) illustrates the conditional independence condition outlined in equation (9).

Before calculating the ATT, the outcome must be shown to be mean independent of the treatment, conditional on the propensity score. Given the conditional independence assumption set out in (9) above, this requires ensuring the covariates Z meet this condition, which is equivalent to achieving "balance" between treatments and their controls. Several balancing tests exist in the literature. The test we use—commonly called regression-based balancing—is suggested by Smith and Todd (2005a) and explained in more detail in Smith and Todd (2005b). The intuition behind this test is that after conditioning on $P(Z)$, any further conditioning on the Z vector should not provide new information on D. In other words we test whether differences exist in Z between the treatment and control groups after conditioning on the propensity score.[4] If differences remain, then this suggests that the propensity score model is misspecified. Following Dehejia and Wahba (2002), we add cross products and squares of covariates to the specification until balancing is achieved.

With these propensity scores in hand, several ways exist to construct the counterfactual or the last term in equation (11), including kernel estimates, which we use in this study. Kernel estimates use a weighted average of all or a subset of control observations to construct the counterfactual for each treated observation. Each treated observation i is paired or matched with some group of comparable j nontreated observations using their respective $P(Z)$. In order to match observations, a weight matrix $W(i,j)$ is constructed from the kernel function $K(\cdot)$. The kernel function we use is the Epanechnikov kernel because it combines desirable properties from the tricube and the normal kernels (Smith and Todd 2005a). This allows the matching of the outcome of the treated individual i's, value of production or y_{1i}, to the "weighted" value of production of the $D = 0$ control group y_{0j}. In addition all treatment observations N_1 are weighted equally in calculating the average treatment impact. This will construct the counterfactual and estimate the average treatment effect of the treated $A\widehat{T}T$. Heckman, Ichimura and Todd (1997) and Smith and Todd (2005a) provide the following formal exposition:

$$(12) \quad A\widehat{T}T = \sum_{i \in \{D=1\}} \frac{1}{N_1} \times \left[y_{1i} - \sum_{j \in \{D=0\}} W(i, j) y_{0j} \right]$$

where,

$$(13) \quad W(i, j) = \frac{K\left(\dfrac{P(Z_j) - P(Z_i)}{h}\right)}{\sum_{k \in \{D=0\}} K\left(\dfrac{P(Z_k) - P(Z_i)}{h}\right)}$$

[4] Operationally, we regress each covariate on the propensity score, the treatment dummy, the propensity score squared and cubed and the propensity score, squared and cubed, interacted with the treatment dummy. The likelihood ratio test of all variables containing the treatment dummy equal to zero provides the test statistic.

and

$$(14) \quad \sum_{j \in \{D=0\}} W(i, j) = 1.$$

As suggested by DiNardo and Tobias (2001), the kernel choice has less impact on the estimated weight matrix, $W(i,j)$, than does the choice of bandwidth (h). More bias and less variance are associated with higher values of h, and less bias and more variance are associated with lower values of h. Following Frölich (2004), the optimal bandwidth is found through the "leave-one-out" method of cross validation. Using various bandwidths, the mean squared error $\frac{1}{N_0}\sum_{j \in \{D=0\}} (y_{0j} - \hat{y}_{0j})^2$ for all observations in the control group (N_0) is minimized where y_j is the value of production for observation j in $D = 0$ and $\hat{y}_j$ is the predicted value of production from the kernel estimator when observation j is left out.[5]

Results

First, the production impacts are estimated using the most common approach in the literature—the maximum likelihood Heckman procedure for treatment effects. Treatment effects are estimated using the ARMS data set and the SCF data set separately due to differences in their data collection procedures. Then, the propensity score-matching method is estimated. The first step of this procedure requires estimation of the propensity score via a logit model that predicts whether or not a sole proprietorship is credit-constrained based on a set of factors that affect the likelihood of treatment (credit-constrained) and factors that affect the outcome (value of production or *VPROD*). Before we estimate the logit model, we drop outliers defined as observations over two standard deviations from the weighted mean *VPROD*.[6] Using the estimated propensity scores, we then estimate the average treatment effect of the treated (*ATT*), using those sole proprietorships who applied for and received credit as the control group and those who were denied credit as the treatment group.

Probability of Being Credit-Constrained Results

The probability of being credit-constrained is estimated via a weighted logit model, with the covariates coming from table 1. Expected signs for these variables were discussed in the data section. In addition to these variables, we include a series of dummy variables representing production specialty for the farm data (e.g., wheat, corn, cattle, etc.) and industry codes for the business data (e.g., wholesalers, personal services, food manufacturing, etc.). Also, total acres (*ACRES*) and regional dummies (Northeast, South, Midwest, Plains, and West) for the farm estimates are included.

Results of the initial specifications of the logit models are given in table 2. Parameter estimates in both models are generally in line with expectations, although the significance of variables differs between data sets. Significant variables from the ARMS data suggest that having greater net worth (*LNBUSNW*) and being in business for more years (*YRBUS*) lower the probability of being denied credit. Significant variables from the SCF data suggest that a greater net worth (*LNBUSNW*), more liquidity (*LIQRESV*), and more employees (*EMPLYNUM*) lower the probability of being denied credit. The lack of college education is positive and significant in both data sets, suggesting household operators without a college education are more likely to be denied credit. Measures of financial well-being—including household income (*LNHHINC*), expected sales price of home (*EXPSALP*), and business net worth (*LNBUSNW*)—consistently reduce the probability of being denied credit in both models.

Impact of Being Credit-Constrained on Production

Table 3 reports the results for the "unmatched," average treatment effect of the treated (*ATT*) kernel-based matching estimate using the Epanechnikov kernel and the maximum likelihood Heckman procedure results for the preferred (turned down for credit) and traditional (turned down for credit and did not apply for credit for the fear of denial) treatment classifications. The "unmatched" differences in the value of production are for the preferred treatment category. These differences are calculated by taking the raw value of production means for businesses from the ARMS data $225,114 in the control group and

[5] For kernel matching the bandwidth grid is $0.01 \times 1.2^{g-1}$ for $g = 1, \ldots, 29$.

[6] Farm data are cut at $785,339 (15% of the sample) and the SCF cut is at $672,873 (16% of the sample).

Table 2. Weighted Logit Estimates for Credit-Constrained Farm and Nonfarm Sole

Variables	Farm Estimates Coefficient	Farm Estimates Standard Error	Non farm Estimates Coefficient	Non farm Estimates Standard Error
Intercept	1.51	1.954	20.957	18.937
Natural log household income	−0.084*	0.046	−0.948	1.264
Natural log business net worth	−0.315***	0.103	−0.446***	0.159
Working capital divided by monthly expenditures	0.018	0.017	−1.538**	0.728
Total operator spouse labor hours	−0.0001	0.0001	0.0001	0.0003
Total weeks spent by operator and spouse working away from the business	−0.0002	0.0002	−0.001	0.001
Number of years owning and operating the business	−0.071***	0.019	−0.156*	0.085
Household head's age in years	0.001	0.021	−0.094	0.089
Number of dependents	0.009	0.111	0.433	0.773
Number of business employees	0.007	0.094	0.047	0.143
Number of loans	0.073	0.107	−0.127	0.116
Expected sale price of dwelling	−0.001	0.001	−0.003	0.003
Dummy variable with 1 being operator and spouse do not have a college education; 0 otherwise	3.091***	0.716	1.448*	0.852
Dummy variable with 1 being household head is single; 0 otherwise	−2.376***	0.826	1.685	1.823
Total acres	−0.0004	0.0003		
Specialty dummies	YES		YES	
Regional dummies	YES			
Pseudo R^2	0.319		0.622	

Note: Significance levels are denoted by triple asterisks (***), double asterisks (**), and single asterisk (*) for 1%, 5%, and 10%, respectively.
Specialty dummies are production types for farm data and industry codes for nonfarm data.
Regional dummies are Northeast, South, Midwest, and West for farm data. Plains is the base.

$163,169 for the treated group (difference of –$61,945). Similarly, in the SCF data the control group raw mean is $154,146, and the treated group mean is $78,615 (difference of –$75,531). The matched weighted means are reported via the *ATT* using the Epanechnikov kernel estimates. In both farm and nonfarm cases the matching estimate eliminated noncomparable observations from the counterfactual; six observations were off the common support in the ARMS data and two in the SCF data.

The difference in means for the matched data is $39,658 for farm sole proprietorships and $57,050 for businesses. Significance of these results is determined using bootstrapped standard errors using 1,000 replications. The bootstrapped standard errors suggest the treatment effect is negative and significantly different from zero at the 5% level for the farm data and at 10% for the business data. The results from these matching estimators suggest that credit constraints significantly and negatively impact the value of production in both farm and business sectors. Aggregating the *ATT* results to a national level for observations on the common support suggests a total loss of output for farm and nonfarm sole proprietorships is only 3% and 13%, respectively.[7]

In general the Heckman procedure tends to overestimate the treatment effect, while the impact based on the traditional treatment definition is smaller in both cases. First, the difference between the *ATT* and Heckman may be due to the Heckman procedure's reliance on functional form restrictions and the inclusion of all observations that fall off the common support. Under the preferred treatment measure (denied credit only) the Heckman

[7] These aggregate results are obtained by taking the *ATT* multiplied by the weighted number of sole proprietorships that were denied credit then dividing this number by the weighted value of production for all sole proprietorships on the common support.

Table 3. Propensity Score-Matching Results for Farm and Nonfarm Sole Proprietorships—Production

Treatment Estimates	Mean Difference in Value of Production[a] Farm Sole Proprietorships	Nonfarm Sole Proprietorships
Preferred treatment classification[b]		
Unmatched sole proprietorships estimate	−\$61,945	−\$75,531
ATT matched estimate[c]	−\$39,658**	−\$57,050*
Maximum likelihood Heckman procedure estimate	−\$100,443**	−\$34,849
Traditional treatment classification[d]		
ATT matched estimate	−\$32,942**	−\$15,816
Maximum likelihood Heckman procedure estimate	−\$80,330**	−\$56,878*

Note: Significance levels are denoted by double asterisks (**) and single asterisks (*) for 5% and 10%, respectively.
[a] Difference is between control and treatment group means. Farm sole proprietorships' control group has 1,515 on and 0 off the common support and the treatment group has 93 on and 6 off the common support. Nonfarm sole proprietorships' control group has 154 on and 0 off the common support and the treatment group has 16 on and 2 off the common support.
[b] Were turned down for credit as treated and did apply and received credit as control.
[c] Average treatment effect of the treated (ATT) is estimated by matching data using the Epanechnikov kernel estimate. The bandwidths are 0.021 for ARMS and 0.169 for SCF for the preferred treatment measure. The bandwidths are 0.039 for ARMS and 0.202 for SCF for the traditional treatment measure.
[d] Were turned down for credit and did not apply for credit for fear of denial as treated and did apply and received credit, did not apply for credit, and were initially denied credit but obtained credit after multiple attempts as control.

procedure estimates the value of production will decrease by \$100,443, while the *ATT* states the impact is \$39,658. The difference between the preferred treatment measure and the traditional treatment measure illustrates that a form of sample bias is present. Using Jappelli's credit-constrained classification in our context would underestimate the *ATT* by approximately \$7,000 and \$42,000 for farm and nonfarm sole proprietorships, respectively.

Other Outcomes of Interest

It is possible that the high capitalization of the farm sector is driving the difference between the *ATT* for farm and nonfarm sole proprietorships. The literature includes debates on whether agricultural subsidies inflate asset prices (such as real estate) thus contributing to this capitalization. To consider this issue, we segment the farm data into livestock and crop producers. Livestock producers are not as highly capitalized, particularly in terms of land, when the full range of productive assets is considered. Nor are they the primary recipients of agricultural subsidies, as compared with crop producers. We follow suggestions from Dehejia (2005) and reestimate the propensity score for each subset of the data, then perform balancing tests as described in the previous section. The *ATT* results for this segmentation are presented in table 4. Credit-constrained livestock sole proprietors and credit-constrained crop sole proprietors

Table 4. Propensity Score-Matching Results for Livestock and Crop Farm Sole Proprietorships—Production

Preferred Treatment Estimates[b]	Mean Difference in Value of Production[a] Livestock Farm Sole Proprietorships	Crop Farm Sole Proprietorships
Unmatched sole proprietorships estimate	−\$76,670	−\$43,394
ATT-matched estimate[c]	−\$76,454***	−\$53,955**

Note: Significance levels are denoted by triple asterisks (***) and double asterisks (**) for 1% and 5%, respectively.
[a] Difference is between control and treatment group means. Livestock farm sole proprietorships' control group has 895 on and 0 off the common support and the treatment group has 50 on and 3 off the common support. Crop farm sole proprietorships' control group has 620 on and 0 off the common support and the treatment group has 44 on and 2 off the common support.
[b] Were turned down for credit as treated and did apply and received credit as control.
[c] Average treatment effect of the treated (ATT) is estimated by matching data using the Epanechnikov kernel estimate. The bandwidths are 0.016 for livestock and 0.552 for crop farm sole proprietorships.
Data source ARMS.

have a statistically significant lower value of production than their noncredit-constrained counterparts. The difference between the *ATT* for credit-constrained crop and livestock producers is approximately $23,000, with crop producers having the lowest *ATT*. This result warrants further analysis since crop producers received, on average, $9,000 more in government payments, and they have a larger investment in capital assets. Potentially, crop producers are using government payments to alleviate credit constraints and/or their investment in real estate makes them more creditworthy.

Segmenting the ARMS data is one way to look at the different effects of being treated, in our case credit-constrained, on the value of production for livestock and crop producers. What about the impact of being credit-constrained on another outcome variable of interest? The value of production may not be the only outcome of interest to policymakers. Providing a "safety net" to farmers is an often-cited objective in farm policy, suggesting policymakers want to ensure a minimum standard of economic well-being for farm households. One measure of economic well-being is household consumption, defined as disposable household expenses or total household expenditures less utilities, home insurance and mortgage/rent payments. Many studies investigating the impact of being credit-constrained have considered consumption as the outcome variable of interest; Phimister (1995), for example, found that credit-constrained farms had lower consumption expenditures. Table 5 shows the *ATT* results for the impact of credit constraints on consumption for farm sole proprietorships.[8] These results show that consumption for credit-constrained farm sole proprietorships is on average $18,377 lower than their noncredit-constrained counterparts. Identifying the reason for the drop in consumption by the farm household is beyond the scope of this article, but differences in consumption suggest another area for future work—the fungibility of business profits and credit between the farm household and its business enterprise(s).

Table 5. Propensity Score-Matching Results for Farm Sole Proprietorships—Consumption

Preferred Treatment Estimates[b]	Mean Difference in Consumption[a]
Unmatched sole proprietorships estimate	−$14,537
ATT matched estimate[c]	−18,377*

Note: Significance level denoted by single asterisk (*) for 10%.
[a] Difference is between control and treatment group means. Farm sole proprietorships' control group has 1,486 on and 0 off the common support and the treatment group has 96 on and 0 off the common support.
[b] Were turned down for credit as treated and did apply and received credit as control.
[c] Average treatment effect of the treated (ATT) is estimated by matching data using the Epanechnikov kernel estimate. The bandwidth is 0.021.
Data source ARMS.

Conclusions and Policy Implications

In this study, we examine two potential forms of bias while evaluating the impact of credit access on the value of production for farm and nonfarm sole proprietorships. The first bias, which we refer to as control group bias, arises from the data classification. Previous studies have collapsed households that obtained credit after multiple attempts and those that had no demand for credit as the control group. This confounds the comparison and potentially biases the estimates of economic impacts. In our "preferred treatment measure," we include only observations that were denied credit in our treatment group and only observations that received credit without issue in our control group. Our results show that control group bias produces lower treatment effects compared to the "preferred treatment measure."

The second bias is selection bias. Selection bias arises because credit-constrained sole proprietors were not randomly selected. The propensity score technique we employ addresses this selection bias and shows that the value of production for credit-constrained farm and nonfarm sole proprietorships decreases by approximately $39,000 and $57,000, respectively. For small and/or beginning sole proprietors, this drop in the value of production could be devastating. Fortunately, the FSA and SBA have programs in place to assist sole proprietorships just starting or facing extreme financial adversity.

Aggregating these impacts to a national level suggests that the total value of production decreases slightly due to farm and nonfarm sole proprietorships being turned down for credit by three and 13%, respectively. This relatively small aggregate impact may be due in part to the majority of farm and nonfarm sole proprietorships receiving credit without issue (54%). This decrease could be further

[8] Survey respondents that refused any portion of the consumption questions were excluded from this estimate.

attributed to the wide availability of credit in a mature credit market such as the United States or simply to the fact that many of the credit-constrained sole proprietorships operate small-scale operations.

By segmenting the farm data into crop and livestock producers, we add empirical evidence to the ongoing debate concerning agricultural subsidies, in particular to the question of decoupled payments and their impact on production decisions (Goodwin and Mishra 2006). Our study found that on average crop farms that receive more agricultural subsidies than their livestock counterparts experience a smaller drop in value of production due to being credit-constrained; existing subsidies may allow crop farms to alleviate credit constraints and achieve higher levels of production. Moreover, while we find only a small aggregate loss in total value of production from credit-constrained operations, the economic well-being of farm households (i.e., consumption) is negatively affected by credit constraints. Safety net programs that stabilize and/or raise incomes may alleviate credit constraints, thereby ensuring a minimum level of consumption. Such programs may thus have a two-fold positive effect on two key outcome variables for farm sole proprietorships—production and consumption.

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